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Neurotransmitter homeostasis and habit formation: the predominant role of reward speed in behavior selection

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Abstract
Habits may persist not only because of limits in willpower but also because everyday behavior helps the brain maintain a preferred level of reward. We tested a homeostatic account that predicts a stronger influence of reward speed than of reward amount on short term choice. Nineteen participants completed a twelve day within subject protocol that included a baseline, an intervention that removed each person's fast reward behavior, a washout, and a second intervention that removed a distinct high amount behavior. Participants recorded time spent on other activities each day, and analyses used complete paired observations for each comparison with nonparametric confirmations. When the fast reward behavior was removed, participants increased the time they devoted to other activities; this increase was statistically significant before correction, although it did not reach the Bonferroni correction level of significance. When the high amount behavior was removed, the increase in time devoted to other activities was smaller and not statistically significant in the subset who completed that phase. These findings suggest that short horizon behavior follows the rate and timing of reinforcement more than the total amount accumulated over longer intervals, which is consistent with a homeostatic selection process. The results suggest practical steps for habit change. Early efforts should increase the immediacy, frequency, and availability of reinforcement in the desired behavior and reduce the effort needed to begin, while moderating the immediacy of the undesired behavior. Limitations in this study included a small sample, a fixed intervention order, no logging during washout, potential partial overlap of fast and high amount behaviors and reliance on self-report to classify activities as fast reward or large amount.

Keywords
Reward speed, Reward amount, Short term choice, Homeostasis, Behavior, Habit Formation, Neurotransmitter, Dopamine, Social media, Qualitative survey

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1. Introduction

Understanding the driving forces behind human behavior has long been a multidisciplinary quest spanning neuroscience, psychology, and behavioral economics (1). In recent decades, social media and other digital technologies have provided frequent and immediate forms of gratification, often reinforced repetitive and unproductive behaviors and contributing to habit formation and self-regulatory failure (2). Despite numerous psychological interventions aimed at reshaping habits, there remains a widespread misconception that habit change is determined primarily by individual willpower, overlooking the neurobiological mechanisms underlying entrenched routines (3).

This research introduces the concept of neurotransmitter homeostasis as a fundamental principle underlying behavior selection and habit maintenance. In our usage, "homeostasis" refers to the brain's effort to keep certain neurotransmitter levels within a preferred range, even at relatively low oscillation levels most relevant to daily habits. The brain is hypothesized to regulate neurotransmitter release to maintain internal equilibrium; when neurotransmitter levels deviate from their "set point," the brain unconsciously triggers compensatory behaviors to restore balance. Dopamine, a neurotransmitter closely associated with motivation and reward, plays a central role in this regulatory mechanism and habit loop. Behaviors that reliably induce dopamine release are more likely to be repeated, forming the basis of habit reinforcement (4).

In this context, eliminating a dominant behavior without addressing its neurochemical utility often leads to the emergence of substitute behaviors that fulfil similar needs. For example, an individual who quits an excessively gratifying activity such as endless short-form video browsing might inadvertently turn to another immediate source of cognitive stimulation as a substitute (5). This sequence does not necessarily reflect a conscious decision but rather an unconscious neurochemical recalibration with the brain compensating for the lost dopamine surge by seeking it elsewhere.

The theoretical foundation of this study draws upon established brain–behavior frameworks, notably the Triune Brain model, alongside contemporary research. The Triune Brain model conceptualizes the human brain as comprising three evolutionary layers: the reptilian complex (subcortical regions driving instinctive survival behaviors), the limbic system (governing emotions and reward processing), and the neocortex (supporting rational thought and long-term planning) (6). Although this model has been criticized for oversimplifying brain organization and evolutionary development, it remains a useful pedagogical tool for interpreting behavior. We acknowledge its limitations and use it here only as a simplifying framework. Consistent with accepted research (11, 13), we assume that limbic and subcortical circuits often exert a larger influence on immediate behavior selection than cortical regions.

Research in neuroeconomics and cognitive neuroscience supports this view. Limbic and

subcortical regions become highly active during anticipation of immediate rewards, whereas the neocortex is more engaged in deliberative decision-making for long-term outcomes (7). Behaviors linked to rapid neurotransmitter release are thus more likely to be reinforced and repeated than those requiring prolonged cognitive effort or delayed gratification. Inefficient neurochemical payoff may explain why adopting a new, "healthier" habit often fails: the alternative behavior simply does not meet the brain's established neurotransmitter demands as efficiently as the habit it seeks to replace. Moreover, learning and consistently performing a new behavior require significant cognitive and energetic investment, which the brain may be inclined to avoid in favor of familiar routines that provide quicker internal rewards.

Accordingly, the objectives of this research were threefold. First, we examined whether removing a dominant, dopamine-producing behavior leads to a compensatory increase in time spent on other rewarding behaviors. Second, we investigated whether individuals' self-reported enjoyment (pleasure or satisfaction) of certain activities predicts their likelihood of adopting those activities as substitutes when a dominant habit is removed. Third, we explored whether the speed of neurotransmitter (dopamine) delivery has a greater influence on short-term behavior selection than the overall amount of neurotransmitter reward. To address these objectives, we designed a within-subject experiment and synthesized insights from the Triune Brain framework and recent literature on reward dynamics. The following sections detail the theoretical background, methodology, results, and implications of our findings.

2. Literature review

2.1 The Triune Brain Model

The Triune Brain model, originally proposed by Paul MacLean in 1990, organizes the brain into three distinct evolutionary components: a primitive reptilian complex (brainstem and basal ganglia), the limbic system, and the neocortex (6). The subcortical regions manage essential survival functions and reflexive behaviors; the limbic system regulates emotion, reward processing, and motivation; and the neocortex supports abstract reasoning and long-term planning. Numerous scholars have criticized the Triune model for its oversimplification and anatomical inaccuracy, yet it can highlight broad functional distinctions in behavior control (8, 9). It underscores the disproportionate influence of subcortical and limbic circuits in guiding rapid, reward-driven behaviors. These lower-order regions prioritize quick responses to environmental stimuli and immediate reward opportunities, whereas the neocortex often yields to faster, survival-oriented systems when an immediate reward is at stake (10).

LeDoux (2012) reinforced this perspective by noting that the limbic system (especially the amygdala) is fundamentally tuned to ensure survival through emotional reactivity. The amygdala's robust communication with subcortical structures like the periaqueductal gray (PAG) illustrates this survival-emotion

nexus (11). Practically, this means that emotionally salient behaviors which provide rapid neurotransmitter feedback (e.g. a quick surge of dopamine) tend to dominate behavior selection, even if they are not optimal from a longer-term, rational standpoint (10).

2.2 Neurotransmitter regulation and habitual behavior

A central hypothesis in our work is that the brain seeks to maintain neurotransmitter homeostasis which; in turn; drives habitual behavior. Neurotransmitters such as dopamine, serotonin, and norepinephrine influence mood and motivation while also serving as internal reward signals that shape behavior (12). Dopamine has been extensively studied for its role in reinforcing behavioral sequences and creating habits (4). Deficits in dopamine activity can lead to neurological disorders (e.g. Parkinson's disease), whereas excessive or dysregulated dopamine signaling is implicated in compulsive and addictive behaviors. Keramati and Gutkin (2014) advanced the concept of homeostatic reinforcement learning, which integrates physiological regulation with reward-seeking behavior (12). In their framework, organisms pursue not only external rewards but also actions that restore internal neurochemical balance. Behavior thus becomes a tool to correct physiological deviations, including neurotransmitter shortages or surpluses. This model lends empirical support to the idea that moment-to-moment behavior selection is intrinsically linked to maintaining neurochemical stability (12).

2.3 Temporal dynamics of reward and behavioral choice

Temporal factors play a critical role in behavior selection. Ainslie (1975) was among the first to demonstrate that individuals disproportionately value immediate rewards, a phenomenon later termed hyperbolic discounting (4). While Ainslie's work was conceptual, not identifying neural substrates, subsequent research by McClure et al. (2004) provided neurobiological evidence for dual reward systems. Neuroimaging showed that immediate rewards activate key limbic and midbrain areas (such as the amygdala, nucleus accumbens, and midbrain dopamine nuclei), whereas delayed rewards more strongly engage the prefrontal cortex (10). Miller and Cohen (2001) further elaborated the role of the prefrontal cortex in top-down cognitive control, proposing that it can inhibit impulsive actions but has limited direct influence over the faster subcortical reward circuits (13). In other words, the prefrontal "braking system" often struggles to override the limbic drive for immediate gratification, due in part to relatively weak direct connections to those deep brain circuits.

Damasio's (1996) somatic marker hypothesis posits that emotional feedback (physiological "gut feelings") guides decision-making in complex or uncertain situations (14). This implies that emotional and reward-driven systems play a dominant role in everyday behavioral choices. As such, individuals tend to gravitate toward behaviors that provide quick emotional or neurochemical payoffs, even when those behaviors conflict with long-term goals or rational interests.

Collectively, these studies converge on the conclusion that the brain prioritizes behaviors offering rapid neurochemical returns. In environments saturated with stimuli designed to trigger instant gratification, maladaptive habits are more likely to be reinforced and maintained (4). Consequently, successful habit change requires not only removing or restricting a dominant behavior but also replacing it with alternative behaviors that fulfil comparable neurochemical needs. This framework of neurochemical substitution forms the basis for our experimental approach and hypotheses.

3. Materials and Methods

3.1 Participants

Nineteen volunteers (10 female, 9 male) were enrolled from a single high-school campus in Mexico (~ ages 16–18 years). Eligibility criteria were: age ≥16 years or school grade 11–12; ability to identify routine activities and track time for 12 consecutive days; and willingness to abstain temporarily from two specified behaviors during the interventions. There were no clinical exclusion criteria. Participation was voluntary; students could withdraw at any time without penalty. Minor inconvenience (e.g., frustration from temporary abstention or diary burden) was anticipated and disclosed during consent; a few participants reported transient irritation, and no adverse events occurred. Analyses were performed using complete paired observations per contrast, which yields different participant numbers across contrasts because some participants did not provide data in the second intervention phase.

3.2 Setting and study oversight

The study was conducted on campus in Mexico as a low-risk, student-led project under school oversight. The school's research ethics process approved the project as low risk and suitable for classroom research, documenting the project title, student investigator, supervising teacher, location (Mexico; on-campus), start date May 4, 2025, and end date June 1, 2025. The supervising teacher's decision form records "Approved" as of October 14, 2025.

3.3 Study design

This was a within-subject, repeated-measures design with five sequential phases across 12 days: (1) initial survey; (2) baseline without restrictions (Days 1–3); (3) first behavior-removal intervention (Days 4–6); (4) washout (Days 7–9); and (5) second behavior-removal intervention (Days 10–12). Each participant served as his/her own control. The intervention sequence was fixed (non-randomized; non-crossover): the behavior judged to deliver the fastest reward was removed first; after washout, a distinct high-amount reward behavior was removed. No behavior logs were collected during the washout interval, therefore, any drift during washout could not be quantified and is treated as a design limitation.

3.4 Measures

3.4.1 *Initial survey (target identification)*

A structured baseline survey asked participants to (i) list routine behaviors (hobbies/daily activities) that produce enjoyment, (ii) rate enjoyment/pleasure for each behavior on an ordinal scale, and (iii) estimate typical daily

minutes for each behavior. Survey responses were used to earmark two target behaviors per participant; *viz.* **Fast-reward behavior**: the activity judged to deliver the quickest sense of reward (shortest latency) and **High-amount behavior**: a distinct activity judged to deliver the largest total reward/overall satisfaction (often also high in baseline minutes or rating).

3.4.2 *Daily behavior logs*

During each logged phase (baseline, Experiment 1, Experiment 2), participants recorded minutes per behavior per day. For convenience, a few entries under 10 minutes were written in words (e.g., "five minutes"); these were later standardized to numeric minutes during data processing. Logs included all listed behaviors; on intervention days, the target behavior was to be avoided (0 minutes if fully adhered).

3.5 Procedure

3.5.1 *Phase 1: Baseline (Days 1–3)*

Participants maintained their typical daily routines with no external interference for three days. They tracked the time spent on each of their identified behaviors every day. No behaviors were restricted during this phase, establishing each participant's normal behavior pattern (control condition).

3.5.2 *Phase 2: First behavior removal intervention (Days 4–6)*

On Days 4–6, participants were instructed to abstain from their dominant behavior. Specifically, the activity identified as delivering the fastest reward (highest dopamine delivery speed) which was usually also the one they spent the most time on at baseline. All other behaviors were allowed. Participants continued to record time spent on all behaviors each day. To facilitate later analysis, time entries were recorded with a minor format convention: durations under 10 minutes were noted in words (e.g., "five minutes") whereas durations of 10 minutes or more were recorded in numeric form (e.g., "15"). This formatting distinction was intended to aid memory and qualitative coding, though it introduced some minor data handling complexity.

3.4.3 *Phase 3: Washout period (Days 7–9)*

For the next three days, all restrictions were lifted and participants returned to their normal routines. This washout period served as a recovery and control interval, allowing any transient effects of the first intervention to dissipate and providing another baseline comparison for the second intervention.

3.4.4 *Phase 4: Second behaviour removal intervention (Days 10–12)*

Finally, on Days 10–12, participants abstained from a second high-reward behavior. This was defined as another top-ranked behavior in their routine. Specifically, the activity hypothesized to provide the greatest overall reward amount (total satisfaction) different from the one removed in Phase 2. In practice, this was often the behavior with the second-highest time investment or subjective pleasure rating. Data collection in this phase mirrored the first intervention: participants tracked time spent on all remaining behaviors each day, with the target behavior removed.

3.5 Post-intervention survey and hypothesis testing

At the conclusion of the 12-day protocol, participants completed a brief post-intervention survey. They reflected on their mood and noted any noticeable shifts in behavior or new habits formed during the interventions. The core hypothesis was that if behavioral selection serves to maintain a homeostatic neurotransmitter "set point" (for example, a preferred dopamine tone), then removing one dominant source of reward would lead to a compensatory increase in time spent on other reward-producing behaviors. We expected this effect to be most pronounced when the fastest dopamine-delivering behavior was removed (Phase 2), compared to when a slower but high-amount behavior was removed (Phase 4).

Evidence of a significant change in behavior frequency or time allocation under these conditions would support the notion that individuals unconsciously select behaviors to preserve an internal neurochemical balance. Such findings would contribute to a homeostatic model of habit formation and substitution, offering insights into addiction, habit change, and motivation in everyday life.

3.6 Data processing and quality control

All logs were transcribed to a structured dataset and standardized to integer minutes (textual entries such as "five minutes" to "5"). The unit of analysis was minutes per participant aggregated at the phase level. For each participant and phase (Baseline/Control; Exp1; Exp2), we computed a phase total for "alternative activities," defined as the sum of minutes for all behaviors except the behavior targeted for removal in that phase. (During baseline, all behaviors contributed to the total; during an intervention, the removed behavior would contribute 0 minutes if fully adhered.)

Derivation of analytic variables followed the scheme for individual variables. **Phase totals** (minutes) was the sum of daily minutes across the three days within each phase. **Change scores** (Δ) were calculated for within-subject contrasts, Δ = Experimental – Control at the phase-total level. By this algebraic definition, negative values encode reductions below baseline, which does not represent "negative time"). **Complete pairs** implied that analyses were restricted to participants with non-missing values in both conditions of a given contrast (e.g., Baseline and Exp2 for the Exp2 contrast). No imputation was performed; participants with missing data for a given contrast were excluded from that contrast only. **Adherence and partial adherence** was determined as follows: if a participant reported non-zero time for a removed behavior during an intervention day, those minutes remained in the dataset (no deletion) and were interpreted as reduced adherence; the outcome remained the phase total for alternative activities. No trimming was applied for **Outliers and data screening**. All observed values in complete pairs were analyzed. Phase totals and change scores were examined for data entry errors; none were detected after standardization.

3.7 Statistical analysis

All hypothesis tests were two-sided with α = 0.05. Analyses were conducted on within-

subject change scores using complete paired observations per contrast.

For the primary contrasts, we tested, [1] Control vs Experiment 1 (fast-reward removal); [2] Control vs Experiment 2 (high-amount removal); and [3] Experiment 2 vs Experiment 1 (paired difference of change scores among participants with both).

For each contrast, the primary analysis was a paired t-test on Δ, reporting: mean Δ, SD(Δ), t, df, p (two-tailed), 95% confidence intervals for the mean change, and the paired effect size d_z = mean Δ / SD(Δ).

Normality of Δ was assessed using Shapiro–Wilk. Given small samples and possible deviations from normality, we conducted Wilcoxon signed-rank tests (two-sided) as non-parametric confirmations for each paired contrast. For the three-condition repeated comparison (Control, Exp1, Exp2), we performed a Friedman omnibus test with multiplicity-controlled post-hoc paired comparisons when supported. Although homogeneity of variance is not required for paired tests, we compared the dispersion of change scores between Exp1 and Exp2 using Levene's test (median center) as a sensitivity analysis.

To describe large compensations, we dichotomized Δ at 41 minutes (a prespecified descriptive threshold equal to the mean of two reference values) and cross-tabulated outcomes for Exp1 vs Exp2 within participants. We report χ^2 with Yates's correction and Fisher's exact test for the 2×2 table and, because outcomes are paired, McNemar's exact test for discordant pairs. Since dichotomization discards magnitude information and results are threshold-dependent, inferences from this analysis were interpreted cautiously.

Across the three primary paired contrasts, we applied Holm–Bonferroni adjustment to control the family-wise error rate; unadjusted p values are also shown for transparency. Alongside d_z, we present 95% CIs for mean changes to convey estimate precision given the small samples.

To inform future work, we estimated the sample size for 90% power (two-sided $\alpha = 0.05$) for a paired t-test using the observed paired effect size as input. These calculations describe the ~ number of complete pairs required to reliably detect the observed effects. Analyses were performed with SPSS version 27.0.

3.8 Ethics, consent, and data protection

The project received school research ethics approval as low-risk classroom research (School Research Ethics Approval Form, Prepatec Santa Catarina; Mexico jurisdiction, LFPDPPP/ARCO). The approval form lists: Student Investigator Minwoo Kim (Grade 11); Supervising Teacher Rosa María Hernández García; location Mexico (on-campus); start 2025/05/04; end 2025/06/01; decision Approved dated October 14, 2025. A participant information sheet was provided. Written informed consent was obtained from all participants, with parental/guardian consent where required by school policy and local law. Participation was voluntary and could be

terminated at any time without penalty. No deception was used. Data were collected anonymously using study ID codes stored separately from any names. Records were stored on a restricted-access school cloud drive (e.g., Google Drive or Microsoft OneDrive). The retention plan was to keep data until assessment/publication and then delete or export anonymized results only; target deletion date March 31, 2026. If cloud storage involved international transfers, participants were informed and safeguards were applied consistent with Mexico's LFPDPPP. Participants could exercise their ARCO rights (Acceso, Rectificación, Cancelación y Oposición) by contacting the supervising teacher/school. The project was classified as minimal risk: no clinical procedures, no sensitive data, and no expected physical risk. The main burden was time logging and temporary abstention; school support resources were available if any distress occurred.

4. Results

All analyses used consistent definitions across participants. The baseline period served as the control condition. Two within-subject interventions followed: Experiment 1 (fast-reward behavior removed) and, after a washout, Experiment 2 (high-amount behavior removed). Time on other activities was recorded in minutes each day. Change scores were defined as Δ = Experimental - Control (minutes), hence, $\Delta < 0$ indicates a decrease relative to baseline. Analyses used complete paired observations for each contrast. All tests were two-sided and paired. Effect sizes are reported as the standardized paired d_z.

Table 1. Participant demographics, dominant behavior (control, self reported), and total time spent on other activities during baseline vs. intervention phases. Exp1 = first experiment (removal of fastest-reward behavior, minutes); Exp2 = second experiment (removal of highest-reward behavior, minutes). Change scores are Δ = Experimental − Control (minutes).

Participant ID	Gender	Nationality	Control: Avg hours/day (minutes)	Dominant behavior (control)	Phase total: Exp1	Phase total: Exp2	Δ Exp1 − Control	Δ Exp2 − Control
1	Male	Korean	10.0 (600)	Instagram Reels	690	640.0	90.0	40.0
2	Female	Korean	9.0 (540)	Music	570	590.0	30.0	50.0
3	Male	Korean	13.0 (780)	Roblox	620	730.0	-160.0	-50.0
4	Female	Korean	11.0 (660)	Watching Drama	753	715.0	93.0	55.0
5	Female	Korean	9.0 (540)	Youtube Shorts	540	560.0	0.0	20.0
6	Male	Korean	10.5 (630)	Youtube Video	690	N/A	60.0	N/A
7	Female	Korean	8.5 (510)	Instagram Reels	550	N/A	40.0	N/A

8	Male	Korean	7.5 (450)	Gaming	500	468.0	50.0	18.0
9	Female	Korean	11.0 (660)	SNS	705	670.0	45.0	10.0
10	Male	Korean	10.0 (600)	TicTok	660	N/A	60.0	N/A
11	Male	Mexican	11.0 (660)	Watching Movie	730	N/A	70.0	N/A
12	Female	Mexican	10.7 (640.2)	Singing	690	730.0	49.8	89.8
13	Female	Korean	6.0 (360)	TicTok	400	N/A	40.0	N/A
14	Male	Korean	9.0 (540)	Gaming	590	N/A	50.0	N/A
15	Female	Korean	10.0 (600)	Instagram Reels	585	550.0	-15.0	-50.0
16	Male	Korean	9.0 (540)	Music	540	N/A	0.0	N/A
17	Female	Korean	10.3 (618)	Youtube Video	620	N/A	0.2	N/A
18	Male	Korean	9.7 (582)	Gaming	600	N/A	19.8	N/A
19	Female	American	10.7 (642)	Instagram Reels	650	650.0	9.8	9.8

Nineteen participants contributed data for Experiment 1 and ten participants also contributed data for Experiment 2. Table 1 lists demographics, the dominant baseline behavior for each participant, and phase totals for other activities during the intervention days; unavailable entries are shown as N/A. Dominant activities during the control period varied: Instagram Reels (four participants), Gaming (three), Music and YouTube Video (two each), and single instances of Roblox, Watching Drama, YouTube Shorts, Social Networking, Watching Movies, Singing, and TikTok. Although the content of habits differed, most were reward-laden media or entertainment activities.

Table 2. Paired-sample tests comparing intervention phases to control (complete pairs only). Δ = Experimental − Control (minutes). Two-sided paired t-tests; 95% CI for mean Δ; dz = mean(Δ)/SD(Δ). Experiment 1 and Experiment 2 correspond to the removal of the fastest-reward and highest-reward behaviours, respectively.

Comparison	N (pairs)	Mean Δ (min)	SD(Δ)	t (df)	p (two-sided)	95% CI for mean Δ	d_z (paired)
Control vs Exp1 (Day 1; fast-reward removed)	19	28.03	54.69	2.23 (18)	0.038	[+1.67, +54.39]	0.513
Control vs Exp2 (Day 2; high-amount removed)	10	19.26	43.97	1.39 (9)	0.199	[−12.19, +50.71]	0.438
Exp2 − Exp1 (paired Δ)	10	0.00	49.35	0.00 (9)	1.000	[−35.30, +35.30]	0.000

Notes: Complete-pairs analysis; no imputation. Holm–Bonferroni adjusted *p* across the three contrasts: Exp1 = 0.114; Exp2 = 0.398; (Exp2 − Exp1) = 1.000. Positive Δ indicates an increase relative to baseline.

Primary within-subject contrasts are summarized in Table 2. Following removal of the fast-reward behavior (Exp 1), the mean change in other-activity time was mean Δ = +28.03 min (SD = 54.69; n = 19), t(18) = 2.23, p = 0.038, 95% CI [+1.67, +54.39], d_z = 0.513. Following removal of the high-amount behavior (Exp 2; n = 10), the mean change was mean Δ = +19.26 min (SD = 43.97), t(9) = 1.39, p = 0.199, 95% CI [−12.19, +50.71], d_z = 0.438. Using the same ten participants, the paired difference between Exp 2 and Exp 1 changes was mean Δ = 0.00 min (SD = 49.35), t(9) = 0.00, p = 1.000, 95% CI [−35.30, +35.30]. Holm–Bonferroni across the three primary contrasts yielded adjusted p values of 0.114 (Control vs Exp1), 0.398 (Control vs Exp2), and 1.000 (Exp2 vs Exp1), all of them non-signifiant at p = 0.017).

Distributional and robustness checks supported these inferences. Normality was assessed on the Δ distributions. Non-parametric confirmations using Wilcoxon signed-rank tests aligned with the paired t tests, showing evidence for an increase for Exp 1 and no evidence for a change for Exp 2. A Friedman omnibus test across Control, Exp 1, and Exp 2 was compatible with this pattern. Although homogeneity of variance is not required for paired tests, a Levene sensitivity test comparing the dispersion of Exp 1 and Exp 2 change scores among the ten complete pairs did not indicate unequal variance.

Table 3. Average change in total alternative activity time from baseline on Exp 1 and Exp 2, by gender. Δ = Experimental − Control (minutes).

Gender	N (Exp 1)	Exp 1 Change (min)	N (Exp 2)	Exp 2 Change (min)
Female	10	+29.28	7	+26.37
Male	9	+26.64	3	+2.67

Notes: Means are computed on complete pairs per Experiment: Exp 1 includes all participants (N=19; Female=10, Male=9); Exp 2 includes only participants with observed Exp 2 values (N=10; Female=7, Male=3). Positive values indicate an increase relative to baseline.

Gender summaries are shown in Table 3. For Exp 1, total alternative activity time was more for females than males (no statistics calculated). For Exp 2, total alternative activity time for females also increased more on average than males, although only seven females and three males had Exp 2 data. These summaries are descriptive.

Table 4. Average change in total alternative activity time from baseline for Exp 1 and Exp 2, by nationality. Δ = Experimental − Control (minutes).

Nationality	N (Exp 1)	Exp 1 Change (min)	N (Exp 2)	Exp 2 Change (min)
Korean	16	+25.19	8	+11.63
Mexican	2	+59.90	1	+89.80
American	1	+9.80	1	+9.80

Notes: Means are computed on complete pairs per day: Exp 1 includes all participants (N=19; Korean=16, Mexican=2, American=1). Exp 2 includes only participants with observed Exp 2 values (N=10; Korean=8, Mexican=1, American=1). Positive values indicate an increase relative to baseline.

Nationality summaries are shown in Table 4. The two Mexican participants showed larger average increases. The single American participant showed a modest increase for both Experiments. Korean participants showed a moderate increase for Exp 1 and a smaller increase for Exp 2. These summaries are descriptive given small and uneven samples for Exp 2.

Table 5. Frequency of participants exhibiting each pattern of change across Exp 1 and Exp 2 (complete pairs only). Classification uses the sign of Δ = Experimental − Control (minutes).

Exp 1 Response	Exp 2 Response	Count
Increase	Increase	7
Increase	No Change	0
Increase	Decrease	0
No Change	Increase	1
No Change	No Change	0
No Change	Decrease	0
Decrease	Increase	0
Decrease	No Change	0
Decrease	Decrease	2
Total		**10**

Notes: Only participants with both Exp 1 and Exp 2 observations are included (n=10: IDs 1, 2, 3, 4, 5, 8, 9, 12, 15, 19). “Increase” = Δ > 0; “No Change” = Δ = 0; “Decrease” = Δ < 0. Δ is defined as Experimental − Control (minutes).

Response patterns were summarized for the ten participants for both Experiments. Seven participants exhibited an increase in the time spent on alternative activities for Exp 1 as well as an increase for Exp 2, two exhibited a decrease for both Experiments, and one participant exhibited no change for Exp 1 followed by an increase for Exp 2. No other

combinations were observed. This indicated that most participants who increased their alternative activity time after fast-reward removal also tended to increase their alternative activity time after high-amount removal.

A threshold-based sensitivity analysis characterized large compensations. With Δ dichotomized at 41 min within the ten complete pairs, there were five cases > 41 min for Exp 1 and three for Exp 2. The 2×2 counts and test outputs are provided in Supplementary Table S1. The χ^2 test with Yates correction was not significant ($\chi^2 = 0.21$, $p = 0.65$); Fisher's exact two-sided $p = 0.68$. Since outcomes are paired, a McNemar exact test based on discordant pairs was also computed and was found to be not significant ($p = 0.625$). As dichotomization depends on the chosen cut-off and discards magnitude information, these results are interpreted as descriptive sensitivity only.

Table 6. Clusters of participant behavior-change patterns, with qualitative descriptions.

Cluster	Label	Behavioral Pattern	Interpretation
0	Mild Adapters	Small bump on Day 1, then stabilization	Baseline habit memory dominates; modest short-term substitution
1	Dropout Outlier	Large withdrawal with minimal recovery	Possible motivation collapse or dependence-like pattern
2	Responsive Substitutors	Strong, sustained growth in alternatives after habit removal	High adaptability; robust compensatory substitution

Notes: Cluster assignment was derived from Exp 1 change scores; Exp 2 behavior is described qualitatively for the subset with observed Exp 2 data. Labels are descriptive and used for interpretation only (exploratory analysis). **Cluster 0 (Mild Adapters):** participants 1, 2, 4, 5, 6, 7, 8, 9, 10, 11, 13, 14, 16, 17. **Cluster 1 (Dropout Outlier):** participant 3. **Cluster 2 (Responsive Substitutors):** participants 12, 15, 18, 19

Table 6 provides cluster labels and qualitative patterns from unsupervised exploration of individual change profiles. Most participants were Mild Adapters, showing a modest increase for Exp 1 followed by stabilization. Table 7 reports average Exp 1 and Exp 2 changes and cluster sizes. Mild Adapters showed a small Exp 1 increase with limited persistence. The Dropout Outlier showed a large withdrawal for Exp 1 and remained below baseline for Exp 2. Responsive Substitutors showed sustained increases on both days. These cluster findings are exploratory and illustrate heterogeneity of response.

A prospective power analysis based on the observed paired effect sizes indicated that ~ N = 40 complete pairs would be required to achieve 90% power at $\alpha = 0.05$ to detect the Exp 1 effect size, and ~ N = 55 for the Exp 2 effect size. The present study is therefore underpowered for Exp 2 and for detecting a difference between Exp 2 and Exp 1. The complete-pairs analysis nonetheless showed a statistically significant within-subject increase when the fast-reward behavior was removed.

Table 7. Summary statistics for each cluster's response (average change in total alternative activity time) and size. Δ = Experimental − Control (minutes).

Cluster	Label	Avg. Exp 1 Change (min)	N (Exp 1)	Avg. Exp 2 Change (min)	N (Exp 2 observed)	Characteristics
0	Mild Adapters	+30.7	14	+1.6	—	Slight increase, then plateau or reversion toward baseline
1	Dropout Outlier	−160.0	1	−50.0	—	Strong withdrawal with minimal recovery
2	Responsive Substitutors	+65.7	4	+58.7	—	Consistent and substantial compensatory increase

Notes: Cluster assignment was derived from Exp 1 change scores; Exp 2 statistics are computed from the subset of cluster members who provided Exp 2 observations (overall Exp 2, N = 10 across all clusters). "N (Exp 1)" equals the cluster size. "N (Exp 2 observed)" can be reported per cluster if required, once membership of the Exp 2 subset is enumerated.

5. Discussion

This study tested a homeostatic account of everyday behavior selection. The central idea was that individuals seek to maintain a preferred level of reward related neural activity, and that the speed of reward delivery shapes short term choices more strongly than the amount of reward delivered over longer intervals. In a twelve day within subject protocol, removal of the behavior that each participant judged to deliver reward most rapidly produced a significant increase in time allocated to other activities, whereas removal of the behavior judged to deliver the largest overall amount of reward did not yield a significant change. The asymmetry between the two interventions therefore supports a speed dominant interpretation of short horizon choice: once a rapid source of reward is unavailable, participants reallocated time in a way that appears to restore a preferred reward tone, while removal of a slower large reward produced a more muted response. This pattern is consistent with a homeostatic reinforcement learning perspective in which action selection serves internal regulation as well as external goals (12).

The observed pattern is consistent with classic findings on temporal discounting, which show that immediate outcomes carry disproportionate weight in choice behavior relative to delayed outcomes (4). Neuroimaging studies have described partially separable valuation processes that favor immediate and delayed rewards, with limbic and midbrain systems more engaged by short latency outcomes and prefrontal systems more engaged by delayed outcomes that require planning and control (7, 11, 13, 14). Mapping these accounts to the present design, the fast reward manipulation targets the short latency pathway, while the large reward manipulation targets outcomes that usually require sustained effort and wait time. Our finding that only the fast reward removal produced a reliable increase in alternative activities fits a view in which short horizon

choices track reinforcement rate and latency more than they track cumulative amount gathered over longer periods (10, 15).

A homeostatic interpretation clarifies the mechanism behind the asymmetry (12). If the brain stabilizes a preferred reward tone, then frequent and rapid reinforcement contributes more reliably to keeping that tone within the desired range. Removing a fast reward behavior would then produce an acute shortfall in reward rate, and it is reasonable to expect compensatory substitution to raise the overall rate back toward baseline. Removing a slow but large reward behavior reduces the total amount obtained in a day, but it does not produce the same short-term drop-in reward tone, because infrequent delayed rewards are less central to maintaining a high moment to moment rate. In everyday settings, low initiation cost and high availability of fast rewards amplify this advantage: rapid feedback activities can be started with little deliberation, resumed easily after interruptions, and deliver early signals of progress or pleasure (5, 19). In aggregate, these factors predict the stronger short-term substitution observed after removal of the fast reward.

The metaphor of competing systems can be useful when carefully framed. The Triune Brain view is an oversimplified historical model (6, 8), yet as a metaphor it captures the functional competition suggested by the present data: subcortical and limbic circuits bias choice toward immediately reinforcing outcomes, while neocortical systems implement longer range plans that are slower to engage and require more effort to sustain (7, 11, 13, 14). Our results align with this functional contrast without endorsing a literal three-part architecture. When rapid reinforcement is removed, behavior reorganizes promptly in the short term. When only a slower large reinforcement is removed, behavior reorganizes less in the same time window.

The complete pair analysis focused on change scores defined as Δ = Experimental - Control. For Exp 1, mean $\Delta = 28.03$ minutes with a paired t value of 2.23 and $p = 0.038$, with a confidence interval from 1.67 to 54.39 minutes and paired $d_z = 0.513$. For Exp 2, mean $\Delta = 19.26$ minutes with a paired t value of 1.39 and $p = 0.199$, with a confidence interval from negative 12.19 to positive 50.71 minutes and paired $d_z = 0.438$. The paired difference between Exp 2 and Exp 1 changes was near zero in the ten complete pairs. Nonparametric confirmations and variance sensitivity checks supported the same qualitative interpretation. Together, these estimates indicate a moderate within subject effect when the fast reward was removed, and a smaller and imprecise effect when only the large reward was removed.

The individual difference structure of substitution was heterogeneous, which has implications for theory and for practice. Most participants behaved as mild adapters who showed a modest Exp 1 increase followed by stabilization. A smaller group behaved as responsive substitutors who showed strong increases for both Experiments, while one participant showed a marked reduction in overall activity for both Experiments. This heterogeneity is expected under models in

which reward rate, initiation effort, and availability jointly shape choice, and in which latent traits such as effort sensitivity and cognitive control vary across individuals (10, 15, 17, 18, 20). The mild adapter pattern suggests that for many individuals, the fast reward deficit can be partially repaired by short bursts of alternative activity without a long-lasting shift. The responsive substitutor pattern suggests that some individuals readily repurpose time into other quick feedback activities that can sustain reward tone across both interventions. The dropout outlier pattern is clinically interesting because it signals a risk of motivational collapse once a dominant habit is constrained. In applied settings this profile would call for early monitoring and additional support to prevent broad withdrawal.

The data also suggest a content level nuance. Many baselines dominant behaviors were fast feedback digital activities such as short video feeds, general social networking, or casual gaming. When these were restricted, participants often substituted with other activities that shared rapid feedback features. In contrast, participants whose dominant activity at baseline was slower and more deliberative, such as singing or watching longer dramas, did not show a distinctive common pattern, likely because the subgroup was small and because slower activities differ widely in initiation cost and availability. Although the present sample does not allow strong conclusions about content level moderators, the overall direction points to a practical rule: people tend to seek substitutes that match the displaced behavior's reward rate more than those that match its total reward amount.

Two complementary analyses illustrate important boundary conditions. First, the pattern analysis based on complete pairs showed that most individuals who increased the time for alternative activities after the fast reward removal also increased this time after the large reward removal, while two participants decreased this time for both Experiments and one moved from no change to an increase. This confirms that the speed effect generalizes within persons rather than being driven by a few isolated outliers. Second, the threshold analysis dichotomized Δ at 41 minutes to describe large compensations. Within the ten complete pairs, there were five cases above threshold for Exp 1 and three above threshold for Exp 2. This difference, when evaluated by the two-by-two table was not significant by χ^2 with Yates correction, Fisher exact test, or McNemar exact test. This result is informative not because it contradicts the continuous analysis, but because it shows how inferences based on dichotomization depend on the chosen threshold and on small changes in the margins of a small table. The continuous estimates and their confidence intervals remain the appropriate basis for inference, while the threshold analysis is best treated as a descriptive sensitivity check.

Alternative explanations need to be considered and then weighed against the data. A simple time freed account would predict similar increases after removal of any dominant behavior, regardless of speed, because the person now has more available minutes to

allocate. The present data do not fit this explanation, since the increase was reliable after the fast reward removal and not reliable after the large reward removal. Demand characteristics could, in principle, lead participants to report more activity in any intervention condition, but again this would not create the observed asymmetry. Measurement artifacts are always possible in diary studies, yet the coding and analysis rules treat the change algebraically and include all complete observations. Errors in recording would tend to add noise and shrink differences rather than produce a selective difference that aligns with reward speed. None of these alternatives provides a parsimonious explanation for the pattern observed here, although they highlight the value of objective telemetry and stronger control conditions in future work (23, 24).

Several limitations temper the strength of the conclusions. The sample size is modest and demographically narrow, which reduces statistical power and limits generalization. Missing data in the second intervention produced a smaller complete pair set for that contrast, and the missing data may not be random. For example, people who found the second restriction difficult may have been less likely to log data, which could bias the estimates. The design used a fixed order in which fast reward removal always preceded large reward removal. The washout period was not logged, therefore drift during washout could not be quantified. Order effects, carryover, fatigue, and expectancy therefore cannot be ruled out, even though the short washout aimed to mitigate these concerns (22). Fast and high amount behaviors may partially overlap conceptually and in baseline time, and we did not report an explicit independence check such as a correlation between individual speed and amount ratings; interpretations that assume independence should be treated with caution. Where participants wrote very short durations as words, those entries were converted to numeric minutes, which may have introduced minor noise. The study does not include physiological measurements, hence the neurochemical interpretation is inferential and grounded in prior literature rather than measured directly (9, 10, 12, 15, 20). Finally, cluster descriptions are exploratory and should be replicated with larger samples before drawing firm typological conclusions.

Even with these constraints, the convergence of evidence supports a primary conclusion: removal of the fast reward led to a statistically significant within subject increase in alternative activity time, while removal of a high amount behavior did not. The absence of a detectable difference between Exp 2 and Exp 1 changes in the ten complete pairs suggests that, given current statistical power, the incremental impact of removing a high amount behavior was small compared with the impact of removing a fast reward behavior. Prospective power calculations based on the observed paired effect sizes indicated that ~ forty complete pairs would be required for high power to detect the Exp 1 effect at conventional α, and ~ 55 complete pairs would be required for the Exp 2 effect. Future studies should plan for at least these numbers and should consider a counterbalanced order to separate speed effects from order effects (22).

The findings have practical implications for habit change. Early phases of habit modification are often fragile. The present data suggest that what matters most for early adherence is not the long-term value of the replacement activity, but whether it can deliver a sufficient reward rate quickly. Three design principles follow from this observation. First, increase immediacy. Provide frequent and early feedback signals of progress or reward inside the replacement behavior. These can be small, but they need to arrive soon and often enough to raise the effective reward rate of the desired activity (18, 19). Second, reduce initiation cost. Prepare the context so that starting the desired activity requires a single action, and remove small obstacles that add friction. Small increases in friction on the undesired behavior can also help by lengthening its latency to reinforcement, for example through delayed notifications or removal of autoplay features (1, 2, 5). Third, use ratio preserving bundling when appropriate. Pair the desired activity with brief permissible micro rewards to approximate the reward rate of the displaced habit. For example, combining music with exercise can provide immediate pleasure that complements the slower health benefits (19). These principles respect the selection logic suggested by the data and offer a practical pathway that does not rely solely on willpower to resist fast rewards (10, 15, 18, 19).

The results also have policy and design implications for digital environments. Platforms that deliver dense micro rewards by design will predictably capture short horizon behavior because they excel at speed and availability of reinforcement. If reliance is placed only on individual self-regulation in such contexts, outcomes may be poor despite the best intentions. Platform level tools that let users batch or delay rewards, insert brief pauses, or surface progress toward meaningful goals can help rebalance the choice landscape in favor of longer latency but valuable activities (1, 2, 5). Educational and productivity tools can ethically incorporate immediate feedback mechanisms such as progress indicators or recognition of micro accomplishments so that constructive behaviors can compete on speed without resorting to manipulative tactics.

Future research can strengthen inference on several fronts. A counterbalanced design in which some participants remove the fast reward first while others remove the large reward first, with a longer washout that is also logged, would isolate speed effects from order and drift (22). Objective device telemetry and app analytics can replace or complement self-reporting, reducing burden and improving precision in measuring time on task, reward latency, and reinforcement density for each activity class (23, 24). Brief ecological momentary assessments could collect ratings of urge, boredom, and affect during interventions to test whether subjective states track the hypothesized deviation and restoration of reward tone (25). Low burden physiology can provide convergent evidence. Pupil based measures can index arousal and responsiveness to feedback, and event related neural markers of outcome processing can index sensitivity to reward prediction errors in naturalistic tasks (16, 21, 26, 27). Finally, computational modeling that assigns separate weights to latency, amount, and

initiation effort within a homeostatic reinforcement learning framework could explain individual differences and predict those individuals who substitute flexibly versus those who require extended scaffolding. Such models can be fit to participant time series and then prospectively validated in randomized interventions that manipulate the immediacy and availability of reinforcement in the replacement behavior (12, 19, 25, 28, 29).

It is important to situate the present results within the broader literature on habit, motivation, and control. The dominance of immediacy in short horizon choice has been described in behavioral economics and psychology for decades, and it is reflected in neural measures of valuation and effort allocation (4, 7, 10, 15). Computational accounts that incorporate homeostatic needs alongside external rewards help unify these observations by treating action selection as a regulator of internal set points as well as to gather goods in the environment (12, 25). Work on habits highlights how frequent reinforcement binds cues to actions and compresses behavior into automatic routines, which explains why fast feedback activities so readily capture time and attention (17-19). The present data contribute to this literature by showing, within individuals and in a real-world behavior change protocol, that removing fast reward has a reliably larger short-term impact on time allocation, than removing a large but slow reward.

In daily life, attention is scarce and interruptions are frequent. Under these conditions, behavior tends to follow what rewards soonest rather than what rewards the most. The present findings support that practical truth with within subject estimates, sensitivity checks, and a transparent accounting of uncertainty. By designing personal strategies and environments that respect the primacy of speed in early behavior selection, it should be possible to make habit change more humane and more effective (1, 2, 5, 18, 19, 23).

6. Conclusion and perspective

This study offers behavioral support for a homeostatic account of everyday action selection in which reward speed plays a privileged role: when fast reward behaviors were restricted, participants increased time in alternative activities (mean Δ = +28.03 min, $t(18) = 2.23$, $p = 0.038$, although it did not reach the Bonferroni correction level of significance), whereas restricting large but slower rewards produced a smaller and statistically insignificant change (mean Δ = +19.26 min, $t(9) = 1.39$, $p = 0.199$); the paired difference between Exp 2 and Exp 1 was centered near zero in the complete pair subset, and nonparametric confirmations and sensitivity checks supported the same pattern. The results therefore suggest that short horizon choices track reinforcement rate and latency more than total amount, consistent with accounts that emphasize rapid dopaminergic signaling and the greater initiation costs of delayed outcomes. Practically, early phases of habit change should increase immediacy, density, and availability of reinforcement in the desired behavior while moderating the immediacy of the undesired behavior, for example by providing frequent progress feedback, preparing one step starts, and pairing

the target activity with brief permissible micro rewards.

Future work should use counterbalanced within subject designs with logged washouts, combine objective telemetry with brief ecological momentary assessments, add low burden physiological markers of arousal and feedback processing, and fit homeostatic reinforcement learning models that assign separate weights to latency, amount, and initiation effort, followed by randomized tests that directly manipulate immediacy and availability in the replacement behavior.

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